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Running Head: Individual Difference in Configural Learning.

Individual Difference in Configural Associative Learning.

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## ABSTRACT

Individuals differ in their ability to acquire associations between stimuli and paired outcomes, an ability that has been proposed to be independent of general metrics of intelligence or memory (e.g., Kaufman, DeYoung, Gray, Brown, & Mackintosh, 2009). The nature of these differences may reflect the type of associative structures acquired during learning, for instance configuring stimuli to facilitate flexible learning and memory. We test the hypothesis that individuals differ in configural associative learning as distinct from simpler (elemental) stimulus-outcome learning. In Experiment 1 participants were screened for attentional scope and we found that attentional scope predicted configural associative learning that could not be explained simply in terms of differences in strength of associative learning. In Experiment 2, attentional scope was trained resulting in a shift in participants' ability to learn about subsequent configurations unrelated to the training material. We discuss how the differences between individual learners reflect differences in configuring rather than simply differences in strength or speed of learning.

## INTRODUCTION

Associative learning is the ability to acquire a link between two or more stimuli, such that the presentation of one stimulus can activate or inhibit the expectation of another. Associative learning is thought to underlie a range of memory and learning capacities, including Pavlovian and instrumental conditioning (Bouton, 1994; Colwill & Rescorla, 1986; Wasserman & Miller, 1997), as well as more general aspects of human performance such as, instrumental or agentic control (Byrom, Msetfi, & Murphy, 2015; Msetfi, Murphy, Simpson, & Kornbrot, 2005), spatial navigation (Buckley, Smith, & Haselgrove, 2015; Pearce, 2009), motivational systems (e.g., appetite; Brunstrom, 2007), as well as response systems related to pathology, such as fear responses to threat (Arnaudova et al., 2013; Duits et al., 2015; Lissek et al., 2009), chemotherapy-induced anticipatory nausea (Hall, Stockhorst, Enck, & Klosterhalfen, 2015; Rodríguez, 2013), and the development and maintenance of substance addiction (Everitt & Robbins, 2016; Hogarth, Balleine, Corbit, & Killcross, 2013; Hogarth & Chase, 2012; Torres et al., 2013). Across all of these phenomena, experimental work suggests that individuals differ in their associative learning (e.g., Murphy & Msetfi, 2014). It is less clear whether these differences represent sources of natural variability in learning or fundamental differences in *how* people learn, such as differences in how associations develop and what form the associations might take.

The role that configuring plays in learning is one area in which significant research has been conducted and differences, thought to relate to underlying neural structures, have been identified (e.g., Fanselow, 1999; Honey, Iordanova, & Good, 2014; Iordanova, Burnett, Aggleton, Good, & Honey, 2009; McDonald et al., 1997).

Evidence from this research with humans and other animals suggests that configuring plays a role particularly where individual cues do not resolve the discrimination. The negative patterning (Whitlow & Wagner, 1972) and biconditional discrimination (Saavedra, 1975) are examples of such problems. In negative patterning stimuli presented alone are paired with one type of outcome (A+, B+) but the combination of stimuli is paired with the absence of outcome or a different outcome (AB-). Since simply summing what has been learnt about the individual stimuli does not provide the correct outcome prediction for compound trials, researchers have sought to understand how associations can be modified to account for accurate performance. Animals (Kehoe & Graham, 1988; McDonald et al., 1997; Whitlow & Wagner, 1972) and humans (Byrom & Murphy, 2014; Harris & Livesey, 2008; Harris, Livesey, Gharaei, & Westbrook, 2008) can readily solve the negative patterning discrimination, biconditional discrimination (i.e., AX+, AY-, BX-, BY+) and other similar problems.

One explanation proposes that, at a peripheral level, the integration of the perceptual input that accompanies stimulus exposure, provides a unique stimulus to support discrimination learning (for review see, Melchers, Shanks, & Lachnit, 2008). For instance, if the two stimuli in a negative patterning discrimination are auditory cues then the compound of the two stimuli may be a perceptually unique new third stimulus (e.g., C) which can become associated with the absence of outcome (ABC-; e.g., Deisig, Lachnit, Sandoz et al., 2003). From this perspective then, configural discrimination does not require a configural processing system. One prediction of this hypothesis is that the extent to which individuals configure will depend critically on the physical characteristics of the stimuli used in the discrimination.

Research has been conducted to test this modality hypothesis, comparing the tendency to configure when stimuli are either from the same or different modalities (e.g., Kehoe, Horne, Horne, & Macrae, 1994; Redhead, 2007). This work generally shows that configuring is facilitated by stimuli from the same modality (Melchers et al., 2008; see also, Soto, Gershman & Niv, 2014). Ultimately though, even with this hypothesis, the ability to configure might be still be expected to vary between individuals by the extent to which an individual peripherally integrated the stimulus input.

Another hypothesis suggests that, somewhat independent of the nature of the stimuli, people vary in how easily or likely they are to configure stimuli; in this sense, configuring is like a mental skill. There is evidence from clinical literature to suggest that individuals differ in their ability to represent or recall configurations of cues. For example, individuals with depression are more likely to recall simple associations rather than complex configural representations when probed for autobiographical memories (Dalgleish et al., 2007; Kuyken & Dalgleish, 1995, 2011; Williams & Scott, 1988). Similarly, anxiety disorders have been linked to an inability to use configural cues, such as contexts, to modulate the associative expectation of threat (Acheson, Gresack, & Risbrough, 2012; van Ast, Vervliet, & Kindt, 2012).

This prompts the question of whether individuals differ in the rate of associative learning per se, or differ specifically in their ability to represent and learn about configurations. Individual difference in the ability to learn about configurations may simply relate to a general difference in the efficiency of associative learning (Kaufman et al., 2009). Indeed, impaired contextual fear conditioning in individuals with high levels of anxiety has been suggested to arise because of a general deficit in associative learning (e.g., Grillon, 2002; Lissek et al., 2009). However, we

hypothesise that individuals differ in their ability to represent and use cue configurations when learning, over and above a difference in simple associative learning. Tests of performance on the negative patterning discrimination have provided support for this hypothesis; individual difference in ability to solve a negative patterning discrimination, requiring use of configurations (A+, BC+, ABC-), can be dissociated from a difference in ability to solve a simple discrimination on the basis of isolated stimuli (D+, EF+, GHI-; Byrom & Murphy, 2014). Thus, testing individual differences in negative patterning suggested that differences in ability to configure stimuli, could be dissociated from general efficiency of associative learning.

The biconditional discrimination, like negative patterning, is one of a class of configural discriminations considered relatively difficult both in terms of solution and interpretation (e.g., McDonald et al., 1997). Research has proposed that some of the difficulty in configural discriminations may reflect individual differences in attention or memory, and further that these differences may reflect fundamental differences in the processing mechanism (Sutherland & Rudy, 1989, Fanselow, 1999) or involvement of specialised neural systems (Honey, Iordanova & Good, 2014, McDonald et al., 1997). For instance, the latter work claims that the mammalian hippocampus plays a central role in solving configural tasks. Another perspective is that these discriminations are diagnostic of the learning and memory processing differences associated with psychopathology. For instance Haddon, et al., (2011) have suggested that failure to learn a biconditional discrimination may reflect the attentional differences demonstrated by people with Schizophrenia.

The current study aims to support the evidence of a difference in configural processing as distinct from a hypothesis that treats configural discriminations as

simply more difficult than other elemental discrimination and further that this difference is flexible and modifiable. Here we employ two experiments, to test this hypothesis, using a set of conditional discriminations that require individuals either (a) to learn about one of three co-occurring cues, while ignoring irrelevant cues (unconditional discrimination) or (b) to learn about configurations of two or three cues (biconditional and triconditional discriminations; see also Shepard, Hovland & Jenkins, 1961). As shown in Table 1, in the unconditional discrimination one of the three stimuli signals the paired outcome, and therefore the discrimination can be solved using associations between single stimuli and their paired outcomes. The unconditional discrimination thus provides an index of simple associative learning. Solving the biconditional and triconditional discriminations requires the co-occurrence of stimuli to be represented so that participants learn about a configuration; simply learning individual associations between each of the co-occurring stimuli and the paired outcome is insufficient. In the biconditional discrimination no single stimulus predicts the outcome, as each stimulus is paired with both outcomes equally. Instead, in the biconditional discrimination, participants need to learn that combinations of two co-occurring stimuli predict the outcome. The triconditional discrimination requires participants to learn that configurations of three co-occurring stimuli predict the outcome. In general, the unconditional discrimination is easiest to acquire, followed by the biconditional discrimination and the triconditional discrimination is the hardest to acquire (Love, 2002; Nosofsky, 1984; Shepard, Hovland, & Jenkins, 1961; Smith, Minda, & Washburn, 2004).

As the difficulty of these discriminations differs we expect to find a general pattern that acquisition of unconditional is stronger than the biconditional which is stronger than the triconditional. However, if individuals differ in their ability to use



configurations, we should see individual differences in the ability to acquire the different discriminations. More efficient associative learning in general would predict better acquisition of *all* three discriminations. However, enhanced configural learning will improve acquisition of the biconditional and triconditional discrimination, but potentially interfere with learning in the unconditional discrimination. Acquisition of the unconditional discrimination should be facilitated by learning about individual stimuli and *not* using configurations.

We are interested in whether, either on the basis of a measure of attentional scope or on the basis of training, individuals differ in their ability to learn these discriminations. Attentional scope refers to a distinction between focusing on fine grained, local or goal relevant details contrasted with a more global focus that captures peripheral and goal irrelevant details (Navon 1977; Lavie 2005). Attentional scope has been implicated in associative learning in general (Acheson et al., 2012; Bar, 2009; Haselgrove & Evans, 2010) and configural learning in particular (Byrom & Murphy, 2014). Further, attentional scope may be particularly relevant for these discriminations, as they vary in the level of relevant and irrelevant information, with no irrelevant stimuli in the triconditional discrimination, one irrelevant stimulus in the biconditional and two irrelevant stimuli in the unconditional discrimination. Shepard et al., (1961) suggested that successful acquisition of these discriminations might relate to selective allocation of attention to relevant stimuli (see also, Kruschke, 1992; Mackintosh, 1975). Narrow attentional scope may be expected to enhance ability to focus on the relevant stimuli and ignore irrelevant stimuli. As such narrow attentional scope should enhance acquisition of unconditional discrimination, but might be expected to interfere with learning the biconditional and triconditional discriminations.

In two experiments we test three hypotheses; (1) that individuals differ in the efficiency of *configural* associative learning, beyond a simple difference in associative learning, (2) attentional scope predicts this difference and, (3) ability to engage in configural as opposed to simple associative learning and vice versa can be trained.

## EXPERIMENT 1

This experiment tests the first two hypotheses, using a within subjects comparison of unconditional, biconditional and triconditional discrimination tasks, as shown in Table 1. Attentional scope was assessed using the Navon task (Byrom & Murphy, 2014; Navon, 1977).

### METHOD

#### *Participants*

Sample size was calculated using effect size estimates ( $f = .39$ ) from prior work in our laboratory (Byrom & Murphy, 2014), to give a power of .98 to find a within-between subjects interaction. The 81 participants (female,  $n = 60$ ) were university students with an average age of 21.80 years. Attentional scope did not correlate with working memory capacity (digit span),  $r(81) = .08$ ,  $p = .47$ .

#### *Design*

A mixed factorial design was employed with discrimination task (unconditional, biconditional and triconditional) and training period (early vs. late) as within subjects factors. The relation between attentional scope and discrimination was assessed.

## **Materials**

All experimental stimuli were programmed and presented using Visual Basic software.

*Discrimination tasks:* Each task included three types of stimuli; a shape (an abstract black shape presented in the foreground), a colour (a background colour), and angled line grating in the background. Each task included eight different stimuli combinations. Three sets of stimuli (Set A, Set B and Set C) were created, with different shapes, colours and angles so that participants completed each task with a different stimulus set. The pairs of black shapes are shown in Figure 1. Colour pairs were yellow vs. red, pink vs. peach, and blue vs. green. The line grating angles were 26° vs. 103°, 51° vs. 129°, and 77° vs. 154°. The use of stimulus set with discrimination task was counterbalanced (i.e., participant one completed unconditional = Set A, biconditional = Set B and triconditional = Set C, participant two completed unconditional = Set B, biconditional = Set C and triconditional = Set A, etc.).

*Navon Task:* Four stimuli were used, consisting of large white letters composed of smaller white letters (e.g., a large H made up of smaller H's) presented on a black background. Stimuli were presented in a square with the large letters spanning 55 mm x 44 mm (6.30° x 5.00°) and the small letters spanning approximately 5 mm x 5 mm (.60° x .60°; see Byrom and Murphy, 2014).

## **Procedure**

After reading an information sheet and having the opportunity to ask questions, participants gave informed consent to participation. Participants

completed an automated programme that included the digit span assessment of working memory (Lezak, 1995), a measure of state anxiety, the Navon task and discrimination tasks. Whether participants completed the Navon task before or after discrimination tasks (task order) was partially counterbalanced, as shown in Table 2.

*Discrimination tasks:* The cover story for the tasks involved stimuli being presented as works of art in a fictitious art gallery. The participants' task was to predict the outcome (stimulus popularity). Participants were informed that the task was in three separate sections with completely independent sets of artwork. Participants completed all three discrimination tasks and discrimination order was partially counterbalanced, as shown in Table 2. The design of the discrimination tasks is shown in Table 1. Each task contained 8 stimuli combinations; four popular (positive outcome) and four unpopular (negative outcome).

For each discrimination, stimuli combinations were displayed 12 times, giving a total of 96 trials. On each trial a stimulus combination was presented and participants were asked to predict the outcome, using a likert scale on the keyboard ranging from 1 (unpopular), through 5 (unsure) to 9 (highly popular). Following the prediction, feedback was presented showing the paired outcome (the stimulus' popularity). This remained on the screen until the participant pressed a button for the next trial.

Feedback was shown visually. Where a stimulus was popular (+) participants were shown a room more than 50% full of people. Where a stimulus was unpopular (-) participants were shown a room that was less than 50% full. Feedback was probabilistic, so that on popular trials the room was shown as 70%, 80% or 90% full,

and on unpopular trials the room was shown as 10%, 20% or 30% full. Probabilistic feedback was used to maintain the participant's engagement with the task.

*Navon task:* This task was used to measure attentional scope (Byrom & Murphy, 2014; Navon, 1977). Participants were informed that they would be presented with a series of large letters composed of small letters and on successive blocks they would be asked to identify the large or small letter presented. Participants completed 8 blocks of 16 trials, each containing 8 "S" stimuli and 8 "H" stimuli, half of these stimuli were incongruent such that large and small letters differed. Stimulus order was randomised within each block and the requirement to identify large or small letters alternated between blocks with half of the participants starting by identifying the large letters.

On each trial, a fixation point was presented in the centre of the screen for 5000 ms, followed by a stimulus presented for 400 ms. A mask replaced the stimulus and remained on the screen until the participant made a response using the S or H key on the keyboard. Following his / her response there was a 3000 ms inter-trial interval. The response time, measured from stimulus onset, and response accuracy were recorded. Attentional scope scores were calculated as the difference in response time on incongruent global ("*identify the large letter*") and local ("*identify the small letter*") trials.

*Data Analysis:* Discrimination scores, were calculated as the prediction of outcome for stimuli paired with outcome (popular) less stimuli paired with no outcome (unpopular). Average discrimination scores were calculated for early (first 6 trial blocks) and late (second 6 trial blocks) training periods. We used regression analysis with late period discrimination scores to assess the relationship between

attentional scope and discrimination. To provide further analysis of experimental effects, we have used a tertile split of attentional scope score to provide dichotomous variables of local attentional scope (range = -26.14 to -2.25;  $n = 27$ ) and global attentional scope (range = 3.56 to 27.44;  $n = 27$ ). Figure 2 shows average discrimination scores. Outcome predictions, across all 12 trial blocks, from which average discrimination scores were calculated, are shown in Figure 3.

An alpha level of .05 was used throughout, with a Bonferroni correction to control for multiple comparisons. We report effect sizes effect sizes ( $\eta_p^2$ ) where key interactions are significant, and report effect sizes and confidence intervals where key simple main effects are significant. For regression analysis we report unstandardized coefficients (B), corresponding confidence intervals and standardised coefficients ( $\beta$ ).

## RESULTS AND DISCUSSION

Discrimination between stimuli improved across training in all three tasks, but this performance was related to individual differences in attentional scope. As shown in Figure 2, individuals with a local attentional scope showed stronger discrimination than those with a global attentional scope in the unconditional task, while individuals with a global attentional scope out-performed those with a local attentional scope in the triconditional task. These observations were verified through linear regression and repeated measures analysis of variance.

Task and discrimination order did not influence attentional scope; univariate analysis of variance of attentional scope showed no effect of task order,  $F(1, 69) < 1$ ,  $p = .380$  or discrimination order,  $F(1, 69) = 1.75$ ,  $p = .135$  and no significant interaction,  $F(5, 69) < 1$ ,  $p = .652$ .

As attentional scope increased, the size of the difference in strength of discrimination between the unconditional and triconditional tasks (unconditional discrimination – triconditional discrimination) decreased. Attentional scope explained a significant proportion of variance in the difference in discrimination,  $R^2 = .05$ ,  $B = -.06$  (.03), 95% CI (-.12, -.004),  $\beta = -.23$ ,  $t(79) = 2.12$ ,  $p = .037$ . The effect of attentional scope remained significant,  $B = -.06$  (.03), 95% CI (-.12, -.004),  $\beta = -.24$ ,  $t(77) = 2.11$ ,  $p = .038$ , when including factors of task order and discrimination order, neither of which predicted discrimination difference ( $t(77) < 1$ ,  $p = .79$ ;  $t(77) < 1$ ,  $p = .95$ , respectively).

The difference between discriminations was driven by the strength of triconditional discrimination increasing with increasing attentional scope;  $R^2 = .06$ ,  $B = .04$  (.02), 95% CI (.003, .09),  $\beta = .24$ ,  $t(79) = 2.12$ ,  $p = .035$ . Further, while simple associative learning, as indexed by discrimination in the unconditional task, did not explain a significant proportion of the variance in triconditional discrimination,  $R^2 = .05$ ,  $B = .21$  (.03), 95% CI (-.005, .362),  $\beta = -.18$ ,  $t(79) = 1.94$ ,  $p = .056$ , attentional scope continued to explain a significant proportion of the variance in triconditional discrimination after accounting for simple associative learning  $R^2 = .11$ ,  $B = .05$  (.02), 95% CI (.007, .087),  $\beta = .25$ ,  $t(78) = 2.35$ ,  $p = .021$ . Attentional scope did not explain a significant proportion of variance in unconditional,  $R^2 < .01$ ,  $B = -.02$  (.03), 95% CI (-.07, .03),  $\beta = -.07$ ,  $t(79) < 1$ ,  $p = .52$  or biconditional discrimination,  $R^2 < .01$ ,  $B < .01$  (.03), 95% CI (-.06, .07),  $\beta = .01$ ,  $t(79) < 1$ ,  $p = .94$ .

Analysis of variance was used to compare performance between tasks in further detail, with the within subjects factors of task (unconditional, triconditional) and training period (early vs. late) and the between subjects factors of attentional scope group (local vs. global), discrimination order and task order suggested group

differences in the acquisition of the discriminations. Both attentional scope groups showed stronger discrimination in the unconditional task than the triconditional task,  $F(1, 48) = 121.19, p < .001, \eta_p^2 = .72$ , but this effect was greater for the local group than global group,  $F(1, 48) = 5.55, p = .023, \eta_p^2 = .10$ . There was no evidence that this interaction differed significantly across periods of training,  $F(1, 52) = 1.72, p = .196$ . For the **local group**, the difference between the discrimination score in the two tasks was  $\bar{X} = 3.39 (.31)$ ,  $F(1, 26) = 121.57, p < .001, \eta_p^2 = .82$ , 95% CI (.66, .88). The difference in discrimination scores between tasks was smaller for the **global group**,  $\bar{X} = 2.21 (.38)$ ,  $F(1, 26) = 33.91, p < .001, \eta_p^2 = .57$ , 95% CI (.28, .71). While discrimination scores in the unconditional task were higher for the local group than the global group, this effect was not significant,  $F(1, 52) = 2.87, p = .096$ . A non-significant trend in the opposite direction was observed with the triconditional task, with higher discrimination scores for the global group than the local group,  $F(1, 52) = 3.16, p = .081$ . There was no main effect of discrimination order,  $F(1, 48) < 1, p = .43$ , and no higher level interactions, all  $F$ s  $< 1.30$ , all  $p$ 's  $< .281$ .

The intermediate group ( $n = 27$ ), scoring between -2.25 and 3.56 on the Navon task, did not differ significantly in comparison of the unconditional and triconditional discrimination over both stages of training from either the local group;  $F(1, 52) < 1, p = .785$ , or the global group;  $F(1, 52) < 1, p = .363$ .

It is possible that this analysis of discrimination scores masks deficits in acquisition of specific stimulus-outcome associations, particularly in the triconditional discrimination. While discrimination scores increased significantly over training for the global group, this may reflect acquisition of only a subset of the 8 stimulus-outcome associations. To test this, we analysed the number of stimulus-outcome



associations acquired. To meet the criteria for acquisition of a stimulus-outcome association, participants were required to give, on at least two consecutive trials, a stimulus paired with a positive outcome a rating of 6 or above or a stimulus paired with a negative outcome a rating of 4 or below. By the end of the 12 blocks of training, the global group had correctly acquired associations for 4.74 (SE = .39) stimuli in the triconditional discrimination and 26% of the global group had acquired outcome pairings for either 7 or 8 of the stimuli. In comparison, by the end of training, the local group had correctly acquired associations for 3.59 (SE = .34) stimuli in the triconditional discrimination and only 11% of the group had acquired outcome pairings for either 7 or 8 of the stimuli. Attentional scope score predicted the number of triconditional stimulus outcome pairings acquired,  $R^2 = .05$ ,  $B = .05$  (.02), 95% CI (.003, .10),  $\beta = .23$ ,  $t(79) = 2.10$ ,  $p = .039$ .

Unconditional discrimination was stronger than biconditional discrimination, which in turn was stronger than triconditional discrimination. Attentional scope predicted triconditional discrimination and explained variance in triconditional discrimination after accounting for simple associative learning, as indexed by the unconditional discrimination. Narrow attentional scope was not related to a general deficit in associative learning; narrowing attentional scope did not relate to a reduction in unconditional discrimination, rather there was evidence of enhanced unconditional discrimination. This suggests that attentional scope relates to individual difference in configural associative learning, rather than simple efficiency of associative learning.

## EXPERIMENT 2

While Experiment 1 used a measure of individual difference in attentional scope, ability to engage in configural associative learning can be influenced by training (for review, see Melchers et al., 2008; Soto et al., 2014). For instance experience solving a task with a configural solution (e.g., A+, B+, X-, AB-, AX+) can facilitate subsequent configural associative learning (Williams & Braker, 1999). Similarly, attentional scope can be trained, through practice attending to details or the global picture (Byrom & Murphy, 2014). In this experiment we sought to test whether the efficiency of configural associative learning could be enhanced or impaired with training.

Participants received training to narrow or broaden attentional scope prior to completing the unconditional and biconditional discriminations. The triconditional was not included as both the biconditional and triconditional discrimination provide tests of configural discrimination. All participants completed both discrimination tasks, with task order counterbalanced.

## **METHOD**

### ***Participants***

Participants completed a Navon training task to train either a local or global attentional scope. The accuracy of performance on the training task provides an indication of how well participants engaged with the training and thus how effective the training was likely to be. The proportion of accurate responses ranged from .49 to 1, with a median accuracy of .96, and mean accuracy of .94 (SD = .08). To ensure that all participants received an adequate level of training, 8 participants with an accuracy of less than .86 (1 SD below the mean) were excluded from subsequent analysis.

The remaining 70 participants (female,  $n = 56$ ) were assigned to local ( $n = 34$ ) or global ( $n = 36$ ) training. Participants were then pseudo-randomly assigned to one of two learning experience conditions; unconditional task first or biconditional task first. As shown in Table 3, there was no evidence that these groups differed in Navon score (prior to training) or digit span, all  $F$ 's  $< 1.00$ , all  $p$ 's  $> .40$ . All participants were university students, with an average age of 22.13 years.

### ***Design and Materials***

A fully factorial design was employed with Navon training (local training, global training) and discrimination task order (unconditional task first, biconditional task first) as the between subjects factor and discrimination task (unconditional, biconditional) as a within subjects factors. The dependent variable was discrimination score, as described in Experiment 1. The stimuli for the discrimination task and Navon task were as described in Experiment 1.

### ***Procedure***

The general procedure was as described in Experiment 1 with the exception of the following changes. All participants completed the Navon task at the start of the experiment to measure attentional scope. Following the Navon task, participants completed attentional scope training to induce either narrow (local training) or broad (global training) attentional scope (see Byrom & Murphy, 2014). The attentional scope training task involved a minimal modification of the Navon task; rather than identifying large or small letters on alternate blocks, participants completing local training were only asked to identify small letters, while participants completing global training were only asked to identify large letters. Following attentional scope training participants completed the unconditional and biconditional discrimination tasks.

## RESULTS AND DISCUSSION

As shown in Figure 5, Navon training influenced discrimination; local training interfered with the acquisition of the biconditional discrimination but enhanced acquisition of the unconditional discrimination, while global training interfered with acquisition of the unconditional discrimination and enhanced acquisition of the biconditional discrimination. These effects were seen in the second task that participants completed. For participants that completed the unconditional discrimination first (see left panel of Figure 5), local training interfered with the acquisition of the biconditional discrimination. For participants that completed the biconditional discrimination first (see right panel of Figure 5), global training interfered with the acquisition of the unconditional discrimination, relative to local training. These observations were supported by analysing the effect of Navon training on unconditional and biconditional discrimination.

Participants acquired both the unconditional,  $F(1, 33) = 326.27, p < .000, \eta_p^2 = .91$ , and biconditional discrimination,  $F(1, 33) = 26.75, p < .001, \eta_p^2 = .45$ , with higher ratings of outcome likelihood for stimuli paired with outcome, than stimuli paired with no outcome. Further, discrimination in the unconditional task was significantly greater than discrimination in the biconditional task,  $F(1, 69) = 80.50, p < .001, \eta_p^2 = .54$ .

Navon training did not have a significant effect on the first task completed; individuals receiving local or global training did not differ significantly on either the unconditional,  $F(1, 36) < 1, p = .389, \eta_p^2 = .02$ , or biconditional discrimination,  $F(1, 30) = 2.73, p = .109, \eta_p^2 = .08$ . Significant effects of training however, were apparent on the second discrimination task completed. Participants with global Navon training

out performed those with local training on the biconditional discrimination,  $\bar{X} = 1.39$  (.62),  $F(1, 36) = 5.07$ ,  $p = .031$ ,  $\eta_p^2 = .12$ , 95% CI (.00, .32). Participants with local Navon training out performed those with global training in the unconditional discrimination,  $\bar{X} = 1.22$  (.50),  $F(1, 30) = 5.95$ ,  $p = .021$ ,  $\eta_p^2 = .17$ , 95% CI (.09, .27).

Navon training influenced both unconditional and biconditional discrimination in the second task completed, with local training enhancing unconditional discrimination, relative to global training and interfering with biconditional discrimination relative to global training. This indicates that, at least short-term changes in configural learning, as distinct from efficiency of simple associative learning, may be trained, through a short and simple intervention.

## GENERAL DISCUSSION

Individual difference in configural learning was assessed in two experiments to test the hypotheses that attentional scope predicts the efficiency of *configural* learning, beyond a simple difference in associative learning and that ability to engage in configural, as opposed to simple, associative learning could be trained. These hypotheses were supported. In Experiment 1; broader attentional scope predicted stronger triconditional discrimination after accounting for simple associative learning. In Experiment 2 participants receiving local training showed stronger discrimination in the unconditional task than participants receiving global training and participants receiving global training showed stronger discrimination in the biconditional task than participants receiving local training.

This pattern of results suggests that individuals differ in *how* they learn, with difference in *configural* learning not accounted for by differences in simple

associative learning. The experimental study of configural discriminations has provided important insights into theories of associative learning, here we provide evidence for these different mechanisms between individuals and within individuals.

Enhanced efficiency of simple associative learning would predict absolute changes in the rate of learning, such that broader attentional scope should be simultaneously related to more efficient triconditional and more efficient uniconditional discrimination. Changes in the efficiency of associative learning can be captured by associative models of learning by changing the learning rate parameter (e.g., Pearce, 1987; Rescorla & Wagner, 1972). Modelling changes in the learning rate parameter predicts the same-direction of effect on the rate for learning for all three discriminations. That is, if we were to suggest that narrow attentional scope related to less efficient associative learning we should expect individuals with narrow attentional scope to acquire all three discriminations more slowly than individuals with broad attentional scope. We found little evidence for such a general difference in associative learning. Instead, narrowing attentional scope predicted a reduction in triconditional discrimination, without any reduction in the ability to solve the uniconditional discrimination. Indeed, there was some evidence that narrowing attentional scope enhanced uniconditional discrimination.

Enhanced configural learning would predict improved acquisition of biconditional and triconditional discriminations, without improved uniconditional discrimination. Solving the triconditional discrimination required participants to learn about the co-occurrence of stimuli. In contrast, learning about the co-occurrence of stimuli in the uniconditional discrimination would result in learning about irrelevant as well as relevant stimuli, retarding acquisition of the discrimination. This pattern of

discrimination related to broader attentional scope. Therefore, broader attentional scope seems to relate to stronger *configural* associative learning.

The current results are consistent with our assessments of configural learning in a negative patterning task; individuals with narrow attentional scope were impaired solving a negative patterning discrimination, compared to individuals with a broad attentional scope (Byrom & Murphy, 2014). Attentional scope did not influence ability to solve a simple discrimination. Further, configural learning could be trained; individuals trained to engage in a broad attentional scope were more efficient solving the negative patterning discrimination than those trained to engage in a narrow attentional scope (Byrom & Murphy, 2014). The results presented here extend these findings in a novel test of configural learning.

Further, our results support previous observation of individual difference in configural learning. Haddon et al., (2014) compared acquisition of a biconditional and uniconditional discrimination and assessed individual difference in relation to schizotypy. Individuals with high scores on the introverted anhedonia subscale of the schizotypy questionnaire (OLIFE; Mason, Claridge and Jackson, 1995), showed disrupted acquisition of the biconditional discrimination, suggestive of a failure to configure stimuli. Interestingly, individuals with elevated schizotypy scores have also shown a bias towards local processing in the Navon task (e.g., Rawlings and Claridge, 1984).

As found in tests of negative patterning, configural learning appears to be trainable. Both here and in our previous study (Byrom & Murphy, 2014), brief attentional scope training influenced configural associative learning, with training to broaden attentional scope enhancing ability to configure stimuli to solve non-linear

discriminations. However, while Navon training influenced both unconditional and biconditional discrimination, the effect of training was not found with the first task completed immediately following the training. It is not clear why effects of training were only seen in the second task.

This may be a consequence that the first discrimination task is somewhat easier than the second because the participants have no prior experience. Indeed, discrimination was significantly stronger on the first task completed,  $t(1, 77) = 2.35$ ,  $p = .021$ . The effect of Navon training may emerge gradually. Alternatively, Navon training may interact with the discrimination experience more specifically. For instance, narrow attentional scope training may provide an advantage, enabling participants to switch back to focusing on a single relevant stimulus and ignore redundant stimuli, following experience that should encourage a focus on multiple co-occurring stimuli (i.e., a biconditional discrimination). A similar effect is plausible to occur in reverse for completing a biconditional discrimination after a unconditional discrimination.

## **Implications**

Individual difference in configural associative learning is rarely tested, but may have important implications for understanding individual difference in the flexibility of learning in general, as well as clinical applications. Flexibility of human learning is an adaptive feature contributing to wellbeing (Beddington, Cooper, Field et al., 2008; Huppert, 2009). For instance, a behaviour that is appropriate in one circumstance may not be appropriate in a similar circumstance. To take an example, it may be appropriate to drink alcohol in the presence of work colleagues on a Friday night at a club, but it may not be appropriate to drink alcohol in the presence of colleagues on



a Monday morning in the office. Simple associations could facilitate learning that drinking alcohol is socially unacceptable and that not drinking alcohol is socially acceptable. Acquisition of a more flexible associative representation requires learning about the co-occurrence of stimuli and paired outcomes.

Narrow attentional scope predicted reduced ability to learn a triconditional discrimination, indicating reduced configural learning. Attentional scope may change with situations, but also reflects a more stable tendency related to high emotional arousal or stress (Cavenett & Nixon, 2006; Easterbrook, 1959; Fredrickson & Branigan, 2005; Mather & Sutherland, 2011) and low mood (Basso, Schefft, Ris, & Dember, 1996; Gasper & Clore, 2002). Reduced configural learning may thus provide a pathway between stress and low mood (associated with narrow attentional scope) and the reduced contextualisation of learning and memory observed in anxiety and depression (e.g., Grillon, 2002; Kuyken & Dalgleish, 2011). As individual difference in the ability to acquire configural associations was not explained simply in terms of difference in the efficiency of associative learning, future research needs to test configural learning to understand how and why individuals differ in their flexibility of learning.

Individual difference in configural associative learning described here is not easily captured in models of associative learning. However, previous studies have illustrated that the physical properties of the stimuli being learnt about can influence the extent to which configural representations are used, with unimodal and integral stimuli facilitating configural associative learning (for review, see Melchers et al., 2008). Following these observations, models of associative learning have been adapted to accommodate variability between simple (or elemental) and configural associative learning (e.g., Honey et al., 2014; Kinder & Lachnit, 2003; Wagner,

2003). These adaptations focus on generalisation between representations; configural learning is enhanced by reduced generalisation between similar representations, such as AXR and AXS. Alternatively, we may think about individual difference in configural learning in terms of differences in sampling capacity, as shown in Table 4 (see also, Byrom & Murphy, 2014). Decreasing sampling capacity, with narrow attentional scope, reduces the probability of sampling a three stimulus configuration and increases the probability of sampling a single stimulus, reducing the efficiency of configural associative learning.

Individual difference in associative learning relates to a wide range of phenomena. Differences in associative learning are often conceptualised in terms of general efficiency of learning. However, general associative learning may be dissociated from configural associative learning. Individuals can differ in configural associative learning and these differences can be trained.

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Table 1: Three conditional discrimination tasks, each using the same stimulus compounds, with each stimulus represented by a letter (e.g., A) and different paired outcomes, where + represents the presence of an outcome and – represents the absence.

Paired outcome			
Stimuli Compound	Unconditional	Biconditional	Triconditional
AXR	+	+	+
BXR	-	-	-
AYR	+	-	-
BYR	-	+	+
AXS	+	+	-
BXS	-	-	+
AYS	+	-	+
BYS	-	+	-

Table 2: Participant data for Experiment 1, split by discrimination order, showing means and standard error. U = Unconditional, B = Biconditional, T = Triconditional. Such that U, B, T refers to participants who completed the Unconditional task, the Biconditional task, then the Triconditional task.

	U, B, T	U, T, B	B, U, T	B, T, U	T, U, B	T, B, U
N	13	15	13	16	16	8
Navon First	2	4	5	5	4	1
Attentional scope	2.86 (2.51)	3.13 (1.26)	-1.35 (2.28)	2.23 (2.46)	-2.34 (2.84)	1.91 (3.61)
Digit Span	7.08 (.61)	6.60 (.70)	7.54 (.18)	6.69 (.66)	7.00 (.53)	5.75 (1.26)

Table 3: Participant data for Experiment 2, split by Navon training group and experience, showing means and standard error.

	Uni-Bi: Local	Uni-Bi: Global	Bi-Uni: Local	Bi-Uni: Global	F test*
Attentional scope	-1.26 (1.86)	-1.87 (2.45)	-.20 (2.13)	2.55 (1.72)	$F < 1, p = .40$
Digit Span	7.72 (.11)	7.80 (.11)	7.82 (.12)	7.72 (.11)	$F < 1, p = .90$

\*df = 3, 65

Table 4: the probability of sampling three dimensions, two dimensions or one dimension from a three dimensional stimulus, as the sampling capacity of a limited capacity buffer increases. These calculations assume each stimulus to be represented by 10 features.

Sampling Capacity of Buffer  (number of features)	Probability of sampling a configuration of...		
	Three	Two	One
	dimensions	dimensions	dimension
	(e.g., AXR)	(e.g., AX)	(e.g., A)
1	0	0	1
2	0	.69	.30
3	.25	.66	.09
4	.49	.48	.03
5	.67	.32	.01
6	.81	.19	0
7	.89	.11	0
8	.94	.06	0
9	.96	.04	0
10	.98	.02	0



Figure 1: The six different black foreground shapes used to create stimuli. The black shapes were one dimension of the stimuli, presented on a coloured background (dimension two) made from angled lines (dimension 3). Within each stimulus set, two different black shapes were used, allowing this dimension to vary between two points.

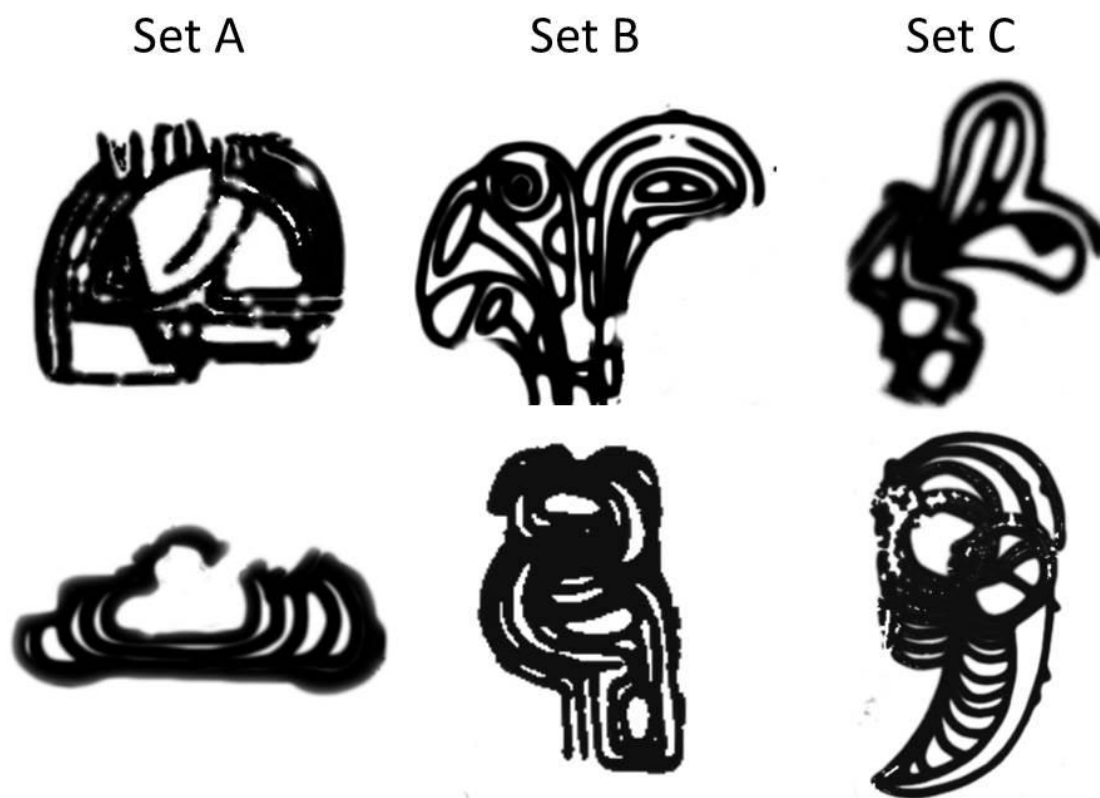


Figure 2: Average discrimination difference scores for Experiment 1, showing local and global participant groups for each of the three tasks across the first and second half of training. Error bars show standard error.

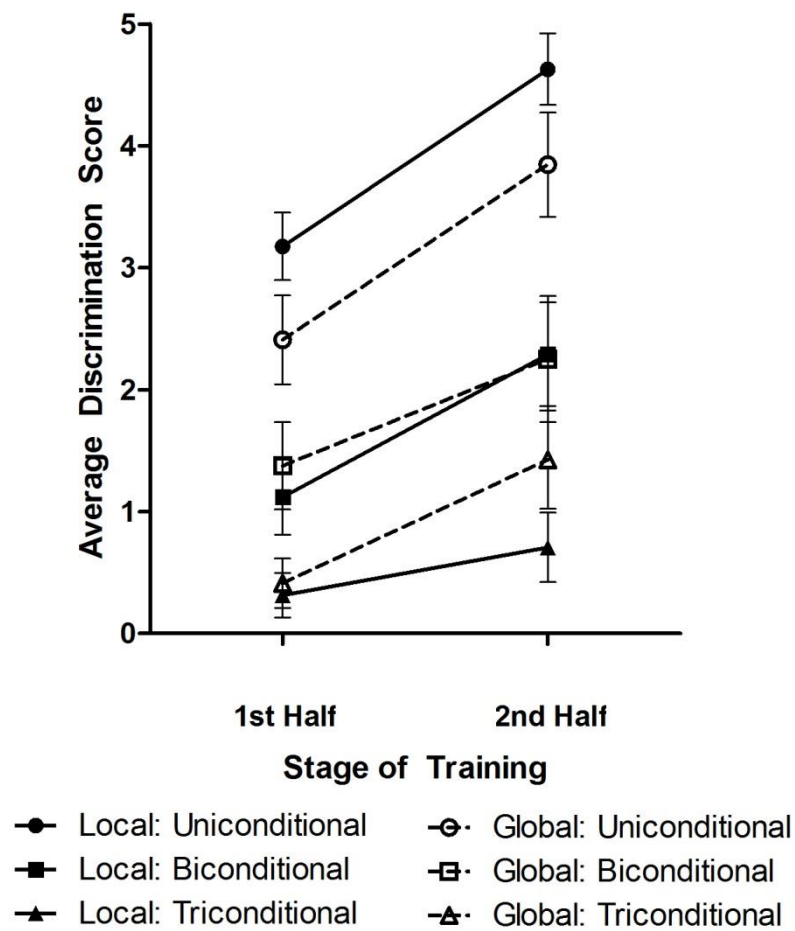


Figure 3: Ratings of outcome likelihood, for all participants, for stimuli paired with a positive outcome (+) and negative outcome (-) for Experiment 1, for unconditional (U), biconditional (B) and triconditional (T) discriminations. Error bars show standard error.

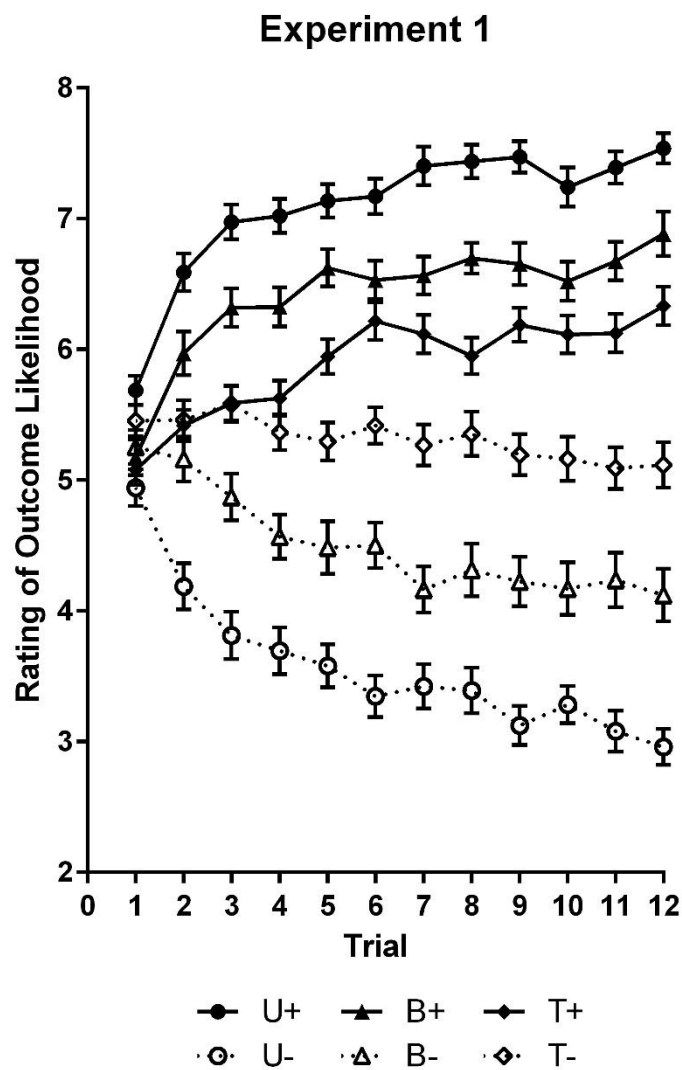


Figure 4: Average discrimination difference scores for Experiment 2, showing local and global training groups for unconditional and biconditional tasks split by the whether this was the first or second task completed. Participants labelled Uni – Bi, completed the unconditional discrimination prior to the biconditional discrimination. Participants labelled Bi – Uni completed the biconditional discrimination prior to the unconditional discrimination. Error bars show standard error.

